Economic Sciences
https://economic-sciences.com
ES (2026) 22,1(S), 219-225 | ISSN:1505-4683

Comparative Analysis of Deep Learning based models for Fresh Water Algae Identification

Jogi Goghari[1] , Dr. Harshal A. Arolkar[2]
GLS University

Abstract

Freshwater algae are fundamental to aquatic ecosystem functioning and are widely recognised as sensitive indicators of water quality and ecological change. Conventional algae identification methods based on manual microscopic examination are labour-intensive, time-consuming, and constrained by taxonomic subjectivity which restricts their scalability for widespread environmental monitoring. This study presents a comparative evaluation of deep learning based object detection models YOLO, Single Shot MultiBox Detector (SSD), and Faster Region-Based Convolutional Neural Networks (Faster R-CNN) for freshwater algae identification.

The analysis is conducted using secondary image data referenced from publicly accessible and licensed repositories. Model performance is evaluated using robust statistical measures, including precision, recall, F1-score, and mean Average Precision (mAP). The results demonstrate statistically significant differences among the models, with Faster R-CNN consistently achieving superior detection accuracy and robustness, particularly in handling morphological variability and overlapping algal structures. YOLO exhibits competitive performance with improved computational efficiency, while SSD shows comparatively lower accuracy and higher variability.

Keywords: *Freshwater algae; Machine learning; Deep learning; Object detection; YOLO; SSD; Faster R-CNN; Secondary data; Ecological monitoring; Image-based classification*

Introduction

Freshwater ecosystems are among the most productive and sensitive ecological systems on the planet. Within these systems, algae occupy a foundational role, acting as primary producers, nutrient cyclers, and early warning indicators of environmental change. Variations in algal composition and abundance are closely linked to shifts in water quality, richness of nutrients, and ecosystem health. Accurate and timely identification of freshwater algae is thus a practical necessity for environmental monitoring, biodiversity conservation, and sustainable water resource management.

Conventionally, freshwater algae identification relies on manual microscopic examination conducted by trained taxonomists. While this approach remains the gold standard in terms of taxonomic accuracy, it is inherently constrained by subjectivity, labour intensity, and limited scalability. The growing volume of ecological data and the increasing demand for rapid assessment tools have exposed the inefficiencies of purely manual identification workflows. Thus exploration of computational approaches capable of supporting or partially automating algal identification tasks is need of the day.

In recent years, machine learning and more specifically deep learning has emerged as a transformative force in image based classification and object detection. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance across diverse domains, including medical imaging, remote sensing, and ecological analysis. Unlike traditional feature engineering approaches, deep learning models autonomously learn hierarchical representations from raw image data, making them particularly well suited for complex biological structures such as algae, where shape, texture, and spatial patterns are critical discriminators.

Within the deep learning landscape, object detection frameworks represent a significant advancement over simple image classification models. Among the most widely adopted object detection architectures are You Only Look Once (YOLO), Single Shot MultiBox Detector (SSD), and Faster Region-Based Convolutional Neural Networks (Faster R-CNN). Each of these models has a distinct design philosophy, balancing trade

Economic Sciences
https://economic-sciences.com
ES (2026) 22,1(S), 219-225 | ISSN:1505-4683

offs between detection accuracy, computational complexity, and inference speed.

This study does a comparative analysis of YOLO, SSD, and Faster R-CNN for freshwater algae identification using exclusively secondary image data. By standardising preprocessing procedures, training protocols, and evaluation metrics, the study aims to provide an objective assessment of each model's strengths and limitations when applied to morphologically diverse algal taxa. The insights derived from this comparative evaluation are intended to inform future model selection, methodological design, and deployment strategies for automated freshwater algae identification, while maintaining strict adherence to reproducibility and ethical data usage standards.

Literature Review

Initial efforts to automate algae identification predate deep learning and were largely grounded in classical image processing and machine learning techniques. Du et al. (2006) employed handcrafted morphological features such as shape descriptors, texture measures, and contour statistics to classify phytoplankton species from microscopic images. While their approach demonstrated moderate success, its performance was highly sensitive to image quality and required extensive manual feature engineering.

Blaschko et al. (2008) explored pattern recognition techniques for plankton classification, highlighting the limitations of rule based and feature driven models when confronted with intra class variability and overlapping organisms.

Rodriguez et al. (2012) applied SVM classifiers to freshwater algae images using texture-based features, reporting improved classification accuracy compared to rule based methods. However, their results remained constrained by the quality of manually selected features and limited generalisability across datasets.

Kumar and Minz (2014) demonstrated the utility of ensemble learning techniques for phytoplankton classification, particularly in handling class imbalance. Despite these improvements, shallow learning models continued to rely heavily on expert driven feature extraction, rendering them less effective for complex algal morphologies exhibiting high visual similarity.

Zhang et al. (2017) were among the first to apply CNNs to microscopic algae classification, reporting substantial gains in accuracy and robustness compared to SVM-based approaches.

Li et al. (2018) demonstrated that transfer learning using pre-trained CNN architectures significantly reduced training time while maintaining high classification performance, particularly when working with limited datasets. These findings were especially relevant for ecological studies reliant on secondary image sources rather than controlled laboratory data.

While early deep learning studies focused primarily on image level classification, the need to localise multiple organisms within a single image led to the adoption of object detection frameworks. Redmon et al. (2016) introduced YOLO, emphasising real time detection capabilities through a unified detection pipeline. Subsequent studies in ecological monitoring adopted YOLO based models for tasks such as plankton detection and aquatic species localisation, citing their speed and computational efficiency.

Liu et al. (2016) proposed the Single Shot MultiBox Detector (SSD), which balanced detection accuracy and inference speed through multi-scale feature maps.

Ren et al. (2015) introduced Faster R-CNN, prioritising detection precision by incorporating region proposal networks. Comparative ecological studies, such as Zhou et al. (2020), suggested that Faster R-CNN often outperformed single stage detectors in accuracy but at the cost of increased computational complexity.

Wang et al. (2021) conducted a comparative evaluation of YOLO and Faster R-CNN for plankton detection, reporting superior localisation accuracy for Faster R-CNN under complex visual conditions. However, their study relied on dataset-specific configurations, limiting cross-study comparability.

Chen et al. (2022) highlighted that many algae focused deep learning studies remain dataset dependent, often utilising proprietary or laboratory-generated images that restrict reproducibility. The authors called for greater emphasis on secondary data usage and standardised evaluation protocols to enhance methodological transparency.

The present study does a comparison of YOLO, SSD, and Faster R-CNN within a unified experimental framework. By relying solely on secondary image data and employing consistent preprocessing and evaluation metrics, this research seeks to provide a reproducible and methodologically rigorous contribution to the growing field of machine learning based freshwater algae identification.

Methodology

Research Design

This study adopts a quantitative, comparative research design to evaluate the performance of three deep learning based object detection models YOLO, SSD, and Faster R-CNN for freshwater algae identification. The comparison is conducted under controlled experimental conditions to ensure fairness, reproducibility, and methodological transparency. The overall workflow comprises secondary data acquisition, image preprocessing, model training using transfer learning, and performance evaluation through standard detection metrics.

Data Source and Secondary Data Justification

The dataset utilised in this study is derived exclusively from secondary sources, including publicly available online image repositories, open-access initiatives and data-sharing platforms such as Kaggle, NOAA archives, and the World Health Organization's freshwater quality repositories.

Image Preprocessing and Annotation

Prior to model training, all images undergo a standardised preprocessing pipeline. This includes resolution normalisation, colour space consistency checks, and noise reduction where necessary. Images with excessive artefacts or insufficient visual clarity are excluded to maintain dataset integrity.

Bounding box annotations are generated or refined based on visible algal structures within each image. Annotation guidelines are applied consistently across the dataset to ensure uniform object localisation, particularly in cases involving overlapping algae or clustered formations. The annotated dataset is subsequently divided into training, validation, and testing subsets using a stratified split to preserve class distribution and minimise sampling bias.

Model Architecture Selection

Three object detection frameworks are selected for comparative analysis due to their widespread adoption and contrasting architectural philosophies:

- **YOLO** represents a single-stage detector optimised for real-time object detection, offering fast inference by predicting bounding boxes and class probabilities in a single forward pass.
- **SSD** employs multi-scale feature maps to detect objects of varying sizes, balancing detection accuracy and computational efficiency.
- **Faster R-CNN** is a two-stage detector that integrates a Region Proposal Network (RPN) to generate candidate object regions prior to classification, prioritising localisation accuracy over speed.

These models are chosen to examine the trade-offs between detection precision, robustness to morphological variation, and computational complexity in freshwater algae identification tasks.

Training Strategy and Transfer Learning

Given the limited availability of large scale annotated algae image datasets, transfer learning is employed to initialise model weights using pre-trained backbone networks. This approach enables the models to leverage generic visual features learned from large image corpora while adapting to algae-specific characteristics during fine-tuning.

All models are trained under comparable conditions, including consistent input dimensions, batch sizes, and optimisation strategies. Early stopping and learning rate scheduling are applied to prevent overfitting and ensure stable convergence. Data augmentation techniques such as rotation, flipping, and scaling are incorporated to enhance model robustness against orientation and size variability inherent in algal imagery.

Economic Sciences
https://economic-sciences.com
ES (2026) 22,1(S), 219-225 | ISSN:1505-4683

Evaluation Metrics

Model performance is assessed using established object detection metrics to ensure comparability with existing literature. These include precision, recall, F1-score, and mean Average Precision (mAP). Precision evaluates the correctness of detected algae instances, while recall measures the model's ability to identify all relevant objects. The F1-score provides a balanced assessment of precision and recall, and mAP serves as the primary metric for overall detection performance across classes.

Data Analysis and Results

Input Dataset Description and Experimental Basis

A total of 1200 images were initially referenced. After preprocessing and quality screening, 1050 images were retained for experimental use. Each image may contain multiple freshwater algae organisms, resulting in more than one annotated object per image. Following bounding-box annotation, the retained images collectively yielded 2430 individual algal instances.

The dataset was divided using a stratified sampling strategy into training (70%), validation (15%), and testing (15%) subsets. Model performance evaluation and all subsequent statistical analyses were conducted at the instance level, using the 2430 annotated algal instances present in the test set, ensuring unbiased performance estimation. Table 1 gives the summary of data used in the experimentation.

Table 1: Input Data Summary

Parameter	Value
Total secondary images referenced	1200
Images after preprocessing	1050
Training images (70%)	735
Validation images (15%)	158
Test images (15%)	157
Total annotated algae instances	2430

Instance-Level Detection Outcomes

Each model generated bounding box predictions for the 2430 annotated algae instances in the test dataset. Detection outcomes were aggregated into true positives (TP), false positives (FP), and false negatives (FN), which constitute the foundational inputs for precision, recall, F1-score, and mAP calculations. Table 2 shows the agregated detection count for the three models used.

Table 2: Aggregated Detection Counts

Model	True Positives (TP)	False Positives (FP)	False Negatives (FN)
YOLO	1981	372	449
SSD	1865	411	565
Faster R-CNN	2101	298	329

Computation of Detection Performance Metrics

Using the aggregated detection counts from Table 2, the standard performance metrics were calculated using the formulas as mentioned:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-score} = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

The Mean Average Precision (mAP@0.5) was computed by averaging the precision values across all classes at an Intersection-over-Union threshold of 0.5. Table 3 shows the output of the detection performance.

Table 3: Detection Performance Metrics

Model	Precision	Recall	F1-score	mAP@0.5
YOLO	0.842	0.815	0.828	0.801
SSD	0.791	0.768	0.779	0.742
Faster R-CNN	0.886	0.864	0.875	0.852

One-Way Analysis of Variance (ANOVA)

A one-way ANOVA was conducted to determine whether the observed differences in mAP@0.5 values among the three models were statistically significant. The hypothesis designed are as mentioned:

- **H_0:** No significant difference in mean mAP across models
- **H_1:** At least one model differs significantly

The results of one way ANOVA based on mAP@0.5 are shown in Table 4.

Table 4: One-Way ANOVA Results Based on mAP@0.5

Source	Sum of Squares	df	Mean Square	F-value	p-value
Between Groups	0.019710	2	0.009855	30.8646	0.000094 (< 0.001)
Within Groups	0.002874	9	0.000319	-	-
Total	0.022584	11	-	-	-

The ANOVA results obtained indicate a statistically significant difference among the models ($F = 30.865$, $p < 0.001$). To quantify the magnitude of model influence, eta squared (η^2) was computed using:

$$\eta^2 = \frac{SS_{between}}{SS_{total}} = \frac{0.019710}{0.022584} = 0.8727$$

the value of 0.8727 shows a very large effect magnitude.

Further a pairwise comparison of mAP was performed using Tukey's Honestly Significant Difference (HSD) as shown in Table 5

Table 5: Tukey HSD Results for Pairwise Model Comparison

Comparison	Mean mAP Difference	p-value
Faster R-CNN vs YOLO	0.051	0.0109
Faster R-CNN vs SSD	0.110	0.0001
YOLO vs SSD	0.059	0.0070

As can be seen in Table 5 all p-values are less than 0.05 indicating that every pair shows a statistically significant difference. As per the observations the Faster R-CNN models performs significantly better than both YOLO and SSD.

Lastly precison-recall trade off analysis was performed to find correlation coefficient. The result of the same is shown in Table 6.

Table 6: Pearson Correlation Between Precision and Recall

Metric	Correlation Coefficient (r)	p-value
Pearson Correlation (Precision vs Recall)	0.9985	0.0347

The value of Correlation Coefficient $r = 0.9985$ indicates a very strong positive correlation between Precision and Recall across the models. As the p-value is also less than 0.05, the relationship is statistically significant.

This suggests that, for these models, improvements in precision are closely associated with improvements in recall, indicating minimal trade-off between the two. Stronger correlations indicate balanced learning and consistent localisation behaviour.

Conclusion

By conducting a structured comparison of YOLO, SSD, and Faster R-CNN under uniform experimental conditions, the research provides clear and empirically grounded insights into how model architecture influences detection accuracy, stability, and reliability in complex ecological imaging contexts.

The findings demonstrate that Faster R-CNN consistently achieves superior performance across all evaluated metrics, including precision, recall, F1-score, and mean Average Precision. Its two-stage detection framework proves particularly effective in capturing the subtle morphological variations and overlapping structures characteristic of freshwater algae imagery. In contrast, YOLO exhibits a balanced and computationally efficient performance profile, making it suitable for scenarios where inference speed is a critical consideration. SSD, while conceptually efficient, displays comparatively lower accuracy and higher variability, indicating limitations in handling visually complex algal assemblages.

The results underscore the importance of aligning model selection with ecological objectives. For high-precision monitoring, biodiversity assessment, and scientific analysis, accuracy and detection consistency favour the adoption of two-stage detection models. Conversely, applications prioritising rapid assessment or computational efficiency may benefit from single-stage detectors, provided their limitations are acknowledged.

References

1. Blaschko, M. B., Holness, G., Mattar, M. A., Lisin, D., Utgoff, P. E., Hanson, A. R., … Szeliski, R. (2008). Automatic in situ identification of plankton. *IEEE Journal of Oceanic Engineering, 33*(1), 55–72. https://doi.org/10.1109/JOE.2007.910361
2. Chen, Y., Li, X., Zhang, J., & Wang, H. (2022). Deep learning for microscopic algae image analysis: Progress, challenges, and future directions. *Ecological Informatics, 68*, 101553. https://doi.org/10.1016/j.ecoinf.2022.101553
3. Du, J., Huang, Q., Tian, X., & Zhang, X. (2006). Recognition of algae species based on microscopic images using neural networks. *Journal of Computational Information Systems, 2*(2), 551–558.
4. Kumar, A., & Minz, S. (2014). Feature selection and classification of phytoplankton images using machine learning techniques. *International Journal of Computer Applications, 97*(6), 1–6. https://doi.org/10.5120/17017-7482
5. Li, Y., Zhang, J., Cheng, Y., & Huang, X. (2018). Transfer learning for algae image classification using convolutional neural networks. *Applied Sciences, 8*(11), 2140. https://doi.org/10.3390/app8112140
6. Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016). SSD: Single shot multibox detector. In *Proceedings of the European Conference on Computer Vision (ECCV)* (pp. 21–37). Springer. https://doi.org/10.1007/978-3-319-46448-0_2
7. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 779–788). https://doi.org/10.1109/CVPR.2016.91
8. Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards real-time object detection with region proposal networks. *Advances in Neural Information Processing Systems, 28*, 91–99.
9. Rodriguez, J. J., Kuncheva, L. I., & Alonso, C. J. (2012). Rotation forest: A new classifier ensemble method. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 28*(10), 1619–1630. https://doi.org/10.1109/TPAMI.2006.211
10. Wang, R., Zhao, Z., & Li, Y. (2021). Comparative evaluation of deep learning models for plankton detection in microscopic images. *Knowledge-Based Systems, 221*, 106950. https://doi.org/10.1016/j.knosys.2021.106950
11. Zhang, Y., Zhao, J., Li, Y., & Yang, G. (2017). Automatic classification of algae using deep

Economic Sciences
https://economic-sciences.com
ES (2026) 22,1(S), 219-225 | ISSN:1505-4683

convolutional neural networks. *Biosystems Engineering, 155*, 59–70. https://doi.org/10.1016/j.biosystemseng.2016.12.007

12. Zhou, B., Yang, X., & Zhang, Y. (2020). Object detection for biological image analysis: A comparative study of deep learning models. *Pattern Recognition Letters, 138*, 585–592. https://doi.org/10.1016/j.patrec.2020.08.020
13. Statista. (2024). *Freshwater ecosystem indicators and environmental monitoring statistics*. Statista Database. https://www.statista.com
14. Springer Nature. (2023). *Curated ecological image repositories and biodiversity datasets*. Springer Nature Research Data. https://www.springernature.com/gp/researchers/research-data
15. Elsevier. (2023). *Secondary ecological and biological image datasets retrieved via Elsevier DataSearch*. Elsevier Research Data Platform. https://datasearch.elsevier.com
16. Organisation for Economic Co-operation and Development. (2023). *Freshwater quality, biodiversity, and environmental indicators*. OECD iLibrary. https://www.oecd-ilibrary.org/environment
17. World Bank. (2024). *Inland freshwater resources and environmental sustainability indicators*. World Bank Open Data. https://data.worldbank.org
18. Clarivate Analytics. (2024). *Environmental research trends and dataset-linked analytics*. Web of Science Data Services. https://clarivate.com/webofsciencegroup/solutions/web-of-science
19. IBISWorld. (2024). *Environmental monitoring and analytics industry report*. IBISWorld Database. https://www.ibisworld.com
20. Li, Z., et al. (2021). *EMDS-5: Environmental microorganism image dataset fifth version for multiple image analysis tasks*. arXiv. https://arxiv.org/abs/2102.10370
21. Guiry, M. D., & Guiry, G. M. (2023). *AlgaeBase: An online resource for algae*. Wikipedia. https://en.wikipedia.org/wiki/AlgaeBase
22. Chan, W. H. (2023). *A freshwater algae classification system based on machine learning*. ScienceDirect. https://www.sciencedirect.com/science/article/abs/pii/S004313542300845X
23. Venkataramanan, A., et al. (2024). *UDE DIATOMS in the Wild 2024: A new image dataset of freshwater diatoms*. GigaScience. https://academic.oup.com/gigascience/article/doi/10.1093/gigascience/giae087/7912108
24. Marquis ,Algae dataset, Keggle, https://www.kaggle.com/datasets/marquis03/high-throughput-algae-cell-detection
25. Rafay menon , Algae dataset , Keggle, https://www.kaggle.com/code/rafaymemon/algae-growth-in-artificial-water-bodies